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Model comparison of flow through a municipal solid waste incinerator ash landfill

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Abstract

The drainage discharge of a municipal solid waste incinerator (MSWI) bottom ash landfill was simulated using various modelling approaches. Two functional models including a neural networks approach and a hydrological linear storage model, and two mechanistic models requiring physical/hydrodynamic properties of the waste material, HYDRUS5 and MACRO (Version 4.0) were used. The models were calibrated using an 8-month data set from 1996 and validated on a 3-month data set from winter 1994/1995. The data sets comprised hourly values of rainfall, evaporation (estimated from the Penman–Monteith relationship), drainage discharge and electrical conductivity. Predicted and measured discharges were compared.

The discharge predicted by the functional models more exactly followed the discharge patterns of the measured data but, particularly the linear storage model, could not cope with the non-linearity of the system that was caused by seasonal changes in water content of the MSWI bottom ash. The fit of the neural networks model to the data improved with increasing prior information but was less smooth than the measured data. The mechanistic model that included preferential discharge, MACRO, better modelled the discharge characteristics when inversely applied, indicating that preferential flow does occur in this system. However, even the inverse application of HYDRUS5 could not describe the system discharge as well as the linear storage model. All model approaches would have benefited from a more exact knowledge of initial water content.

Keywords: Landfill; Hydrology; Model; Leachate; Drainage; Preferential flow; Discharge; Neural network

1. Introduction

Leachate containment and treatment is the central feature of modern landfill management. Leachate quantity and quality depend on landfill design, filling practice and the physical and chemical characteristics of the wastes. The flow paths and interaction times determine the extent of the leaching process. An understanding of the dependence of landfill leachate quantity and quality has been sought by using a wide variety of different modelling approaches. The water balance approach, which considers various inputs, reservoirs and outputs connected by simple relationships, has found wide application, mainly for municipal solid waste landfills (e.g. Ehrig, 1983; Baccini et al., 1987). Recently, Guyonnet et al. (1998) used another empirical approach by applying linear storagemethodology to the production of

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leachate in a municipal solid waste landfill. A mechanistic approach employing the Richards equation to describe unsaturated flow as a function of meteorological conditions and landfill design is used in the well-known model HELP (Hydrological Evaluation of Landfill Performance, Schroeder et al., 1984). Nixon et al. (1997) describe in a recent review HELP and a number of other complementary models. These models mostly assume the landfilled material to be idealised layers with homogenous properties. Simple modelling approaches are justified by the common lack of required data; while mechanistic modelling approaches can theoretically more closely describe physical processes, providing there is sufficient information.

Mechanistic models typically require input of relevant soil properties and an accurate description of the landfill geometry and the initial and boundary conditions to be able to provide correct simulation results. Notwithstanding the advances made in the areas of inverse modelling and spatial analysis, two limitations found in more theoretically rigorous mechanistic models are frequently encountered. First, the soil and hydraulic parameters needed for sophisticated numerical models are usually well beyond the capacity of real-world practical applications. Second, the spatial variability of natural environment limits the accuracy of applying exact flow theories.

The empirical approach for modelling hydrological processes has advantages in that most of the system properties can be ignored (Schaap and Bouten, 1996). Normally, black-box models are constructed by implementing more or less simple linear or non-linear regression equations that couple input to output. As long as the system does not behave in an entirely chaotic manner, the black box model may well provide an adequate description of the outflow. The linear storage model is one such model. It describes water flow through a hydrological entity in terms of an exponential response of an output to a given input. The rate of the response is the only variable that must be found. Neural network models go one step further because they do not make a priori assumptions about the underlying mathematics. When properly optimised using feed-forward back-propagation networks or radial basis functions, neural networks can approximate any continuous non-linear function with any desired degree of accuracy (Hecht-Nielsen, 1991; Haykin, 1994). As such, neural networks are well suited to implement input–output models (e.g. precipitation and evaporation vs. drainage).

A field investigation of hydrological and geochemical factors controlling leachate quality in a municipal solid waste incinerator (MSWI) bottom ash monofill, Landfill Lostorf in Switzerland, has found that leachate quality is strongly dependent on hydrology (Johnson et al., 1998). Because the landfill is subject to transient periods of rainfall and evaporation, successive wetting and drying cycles of the ash occur, leading to time dependent rates of drainage. There are strong indications of preferential flow and tracer studies have shown that, during rain events, between 20 and 50% of rainwater can pass through the landfill within hours (Johnson et al., 1998). For most components, concentrations of the leachate drainage are diluted as a result of rain events whilst others (Cu or Al), can increase by an order of magnitude (Johnson et al., 1999). Between rain events, the leachate has a fairly constant composition. With an average residence time of 3 years, it is probable that a “quasi” equilibrium between the solid and aqueous phase exists. Since the leachate composition can change so rapidly during storm events, it is important to be able, as closely as possible, to model the response in discharge drainage to rainfall.

This paper should be considered as a comparative study to determine which modelling approach best predicts landfill drainage discharge in Landfill Lostorf in response to rainfall and should provide information as how to best model leachate drainage in cases where little physical information is available. A follow up work dealing with the ability of the models to simulate chemical loads of the drainage water will be carried out later.

We have chosen two empirical and two mechanistic approaches. A neural network approach was chosen (Schaap and Bouton, 1996). A linear storage model adapted from Huwe et al. (1994) with preferential flow was selected as the second empirical method. We chose the HYDRUS5 (Vogel et al., 1996) program as the representative of a class of programs that are mechanistic in nature and are based on a one-dimensional isothermal Darcian flow in a variably saturated rigid porous medium. Darcian flow models are not applicable to situations of preferential flow through porous media. For the landfill under investigation, the existence of preferential flow was a subject of dispute. Depending on one's tendency, observed data could be interpreted to support either the presence of preferential flow, or simply the existence of a hydrologically responsive medium. Through modelling, by programs that account and ignore the presence of preferential flow, it was hoped to establish more support in favour of one or the other argument. A second mechanistic model with preferential flow, MACRO (Version 4.0, Jarvis, 1994), was chosen to test the applicability of such a model to a landfill system. Again MACRO describes one-dimensional isothermal Darcian flow together with preferential flow through macropores under saturated conditions.

2. Data collection and treatment

2.1. The site

Landfill Lostorf, a MSWI bottom ash monofill near Buchs AG, Switzerland, is situated in a disused gravel pit. A liner consisting of 0.8 m opalinous clay supporting a gravel drainage layer (0.2 m) serves to collect the leachate via high-density polyethylene (HDPE) tubing into a shaft. Two geotextiles separate the MSWI bottom ash from the drainage layer and the drainage layer from the clay liner. The landfill has a depth of 6 m and has been successively filled to this depth from east to west in discrete stages (at 6–9 month intervals). The landfill has three compartments with separate leachate drainage. This is achieved by the topography of the liner that is inclined at a gradient of around 4% towards the compartment boundary. The experiments were carried out on the oldest compartment (5850 m^2) of the landfill with MSWI bottom ash produced in 1991. The surface of the landfill has not yet been covered or cultivated so there is direct contact between the atmosphere and the disposed ash. Drilling in the landfill has shown that though the ash is in general unsaturated, ponding does exist. The extent of these formations is unknown. One site of ponding, at the centre of the compartment, has a pumpable water volume of between 100 and 200 l of leachate within an hour.

The average yearly precipitation at the local Swiss Meteorological Association (SMA) station (Buchs/Suhr, approximately 2 km west of the landfill in a comparable geographical location) for the period of 1987 to and including 1996 is 1060 mm. The average rainfall maximum occurs between May and June. The driest period is January–April. The summer rains tend to occur in storm events of high rain intensity.

2.2. Discharge and rainfall

All leachate measurements, unless otherwise stated, were made at the central pump shaft and sampling point indicated in Johnson et al. (1998). Automatic registration of drainage discharge, electrical conductivity and temperature were made over the periods, November 1993–February 1994, November 1994–November 1995 and May 1996–December 1996. Flowtec (DI 652) instrumentation, based on changes in the magnetic field as a function of flow rate, was used to measure discharge. Conductivity and temperature were registered on-line with a combined electrode (WTW LF 196). Average values taken every second were saved to a data logger every 15 min. Because of rapid calcite precipitation in the drainage system and onto the walls of the instrumentation, the instruments had to be rinsed through on a weekly basis. In addition, the drainage system had to be flushed prior to the installation of the equipment in each of the above-mentioned periods. Precipitation measurements were made on site using a tilting-siphon rain gauge. The on-site rainfall measurements were compared to data collected by the Buchs/Suhr SMA station.

2.3. Evaporation

Potential evapotranspiration from the surface of the landfill was estimated using the hourly form of the FAO Penman–Monteith equation (Allen et al., 1994). Hourly values of global radiation, relative humidity, pressure, wind velocity (at 2 m) and temperature were obtained from the SMA at the Buchs/Suhr site and in addition from on-site measurements of temperature, relative humidity and wind velocity in 1996.

The actual evaporation from the bare MSWI bottom ash surface was estimated from the potential evapotranspiration mentioned previously using an empirical approach adopted from Black et al.

(1969). The actual evaporation was assumed to be a function of the surface wetting and thus the number of days between rain events was indexed in order to account for the drying of the surface. The potential evapotranspiration (E_{pot}) was then divided by the square root of the number of days since the last rain event, as suggested by Black and co-workers. However, the values for actual evaporation estimated in this way underestimated the evaporation. The best fit was then sought between the difference in total rainfall and total discharge for 1996 measurement period and the actual evaporation (E) by indexing rains of different intensity (2, 5 and 10 mm day^{-1}) and by empirically changing the power of the day index. It must be noted that no water is taken up or released from the waste over this period. The best agreement was found to be

$$E = \frac{E_{pot}}{d^{0.2}} \tag{1}$$

where d is the number of days after a 5 mm rain event. It must be stressed at this point that such fitting is entirely empirical. Using this empirical correction approach, the total evaporation for the 1996 data sets was corrected from 3960 to 2950 m^3 and agreed well with the difference between rainfall and discharge ($5860 - 2940 = 2950$ m^3). The agreement for the 1995 data set was not as good. The evaporation estimated from rainfall, minus discharge (3490 m^3) was higher than the corrected Penman–Monteith value (3010 m^3).

2.4. Data treatment

Using the data set 29 April to 31 December 1996 (5928 h), the models were calibrated and the parameters were optimised. The models were then used to predict the discharge monitored in the period 1 December 1994 to 7 February 1995 (2125 h). Missing discharge and conductivity data caused by instrumentation failure or de-scaling, were linearly interpolated. Such periods did not exceed 10 h and constituted less than 1% of the data sets. The fit of the modelled to the measured discharge was assessed both qualitatively by visual comparison and quantitatively by estimation of the sum of squares (SSQ).

3. Models and procedures

3.1. Neural networks

Feed-forward back-propagation neural networks consist of an input, a hidden and an output layer all containing “nodes”. The numbers of nodes in input and output layers correspond to the number of input and output variables of the model. The number of hidden nodes can be chosen freely; the optimum number depends on the complexity of the underlying problem and is to be determined empirically (Hecht-Nielsen, 1991).

All input nodes $j = 1\ldots J$, with the input variables $x_1\ldots x_J$, are connected to all hidden layer nodes $c = 1\ldots C$ by means of adaptable connections, or “weights”, w_{jc} which can vary between ∞ and $-\infty$. At hidden nodes, input values and weights are multiplied and summed (Eq. (2)). The result R_c is input to a sigmoid function (Eq. (3)), yielding the hidden node output H_c

$$R_c = \sum_{j=0}^{J} (w_{jc} x_j) \tag{2}$$

$$H_c = \frac{1}{1 + e^{-R_c}} \tag{3}$$

Eq. (2) also uses a “bias” value (x_0) to offset R_c. The x_0 value is always 1 and connected to the hidden nodes via the adaptable weight w_{0c}.

The output nodes $l = 1\ldots L$ operate in the same way as the hidden nodes. The hidden node outputs, H_c, are multiplied by the weights w_{kl} (Eq. (2)), while the model outputs ($\hat{Y}_l$) are produced in the same way as in Eq. (3). Because of the use of a sigmoid function (Eq. (3)), $\hat{Y}_l$ ranges between 0 and 1, which means that output values must be scaled to this domain. In this study we have only one output variable (drainage at time $t + 1$). The weight matrices w_{jc} and w_{cl} represent “knowledge” of the neural network. The initially random weights obtain their final values in an iterative calibration using the backpropagation algorithm described by Rummelhart et al. (1986) or a Levenberg–Marquardt type optimisation (Marquardt, 1963; Demuth and Beale, 1992).

Neural networks were implemented in MATLAB by using the TRAINLM routine of MATLAB’s

Table 1
Length of intervals used for the net precipitation history vector $\boldsymbol{H}_t$ and the results of Level 1–3 models as a function of the number of periods in vector $\boldsymbol{H}_t$. The SSQ values are average sum of squares based on the successful neural network models

Interval	Time intervals (h)			SSQ of model results		
	Begin	End	Duration	Level 1	Level 2	Level 3
1	*t*	*t*-1	1	35.66	0.21	31.14
2	*t*-2	*t*-6	5	33.30	0.19	27.66
3	*t*-7	*t*-24	18	26.57	0.18	19.85
4	*t*-25	*t*-48	24	22.34	0.32	17.24
5	*t*-49	*t*-96	48	15.53	0.24	13.06
6	*t*-97	*t*-168	3 days	11.71	0.19	12.03
7	*t*-167	*t*-336	1 week	6.45	0.15	5.33
8	*t*-337	*t*-504	1 week	7.42	0.14	6.15
9	*t*-505	*t*-672	1 week	7.37	0.14	5.56

Neural Network Toolbox (Demuth and Beale, 1992). Default calibration parameters were used but extra code was added to avoid local minima during neural network optimisation. In this modelling procedure, net precipitation (precipitation minus evaporation) determines the upper boundary condition and drainage (q_o) is a time-dependent non-linear function of the net precipitation. A vector $\boldsymbol{H}_t$ with up to nine partial sums of net precipitation of consecutive time intervals between t and t-4 weeks (see Table 1) was designed. The lengths of these intervals were chosen on an empirical basis. Shorter time intervals near time t were selected to capture the dynamics of the drainage (intervals 8 and 9 did not increase in length). The maximum number of nine time intervals was selected as a compromise between increased accuracy and computational burden.

Three approaches were used to predict $q_{o,t+1}$ in order to take the 'state' of the system into account. In Level 1 the neural network determines the relevant internal state from the net precipitation vector only

$$q_{o,t+1} = f(H_c) \quad (4)$$

In Levels 2 and 3, explicit hydrological information about the landfill was added to the input data. In Level 2 net precipitation history and drainage at time t were used to find $q_{o,t+1}$

$$q_{o,t+1} = f(H_c, q_{o,t}) \quad (5)$$

In Level 3 net precipitation history and storage (W) at time t were used to find $q_{o,t+1}$

$$q_{o,t+1} = f(H_c, W_t) \quad (6)$$

where W_t is a scalar containing the cumulative difference between net precipitation and $q_{o,t}$. Hence, W accounts for the storage of water in the profile; $W = 0$ at $t = 0$.

For Level 1, the number of elements in the vector $\boldsymbol{H}_t$ were increased from one to nine, extending the time period of the data used from one hour to four weeks. The nine neural network models were each calibrated 10 times by invoking different initial weights. Three and six hidden nodes were tested in these procedures in order to assess the requirements for the system being tested. The latter was found to give slightly better results and was used in further calculations. Levels 2 and 3 were explored in a similar way as Level 1 by increasing the length of vector $\boldsymbol{H}_t$ and adding W_t or $q_{o,t}$ to the input data.

3.2. Linear storage model

The linear storage approach used in this study is a simplified version of the "hydrologic catchment model" of Huwe et al. (1994). The latter had been adopted from the original work by Blau et al. (1983). In the linear storage approach, the landfill is assumed to be a single hydrological entity. The model assumes the net input (q_i, mm h^{-1}) to the landfill to be rainfall (q_r, mm h^{-1}) minus evaporation (q_e, mm h^{-1}) and minus the amount of water needed to bring the landfill to its full water storage capacity level ($q_{res} \geq 0$, mm h^{-1})

$$q_i = q_r - q_e - q_{res} \quad (7)$$

A value for the storage capacity, or the amount of water that can be held by the landfill material against the gravity is assumed, and the remaining water flows through the landfill via the matrix and/or the preferential flow paths.

The amount of water in a 1-m^2 column of the landfill material (Q, mm) is a function of the difference between the net amount of water entering the landfill (q_i) and the amount of water leaving the landfill as drainage (q_o, mm h^{-1}).

$$\frac{dQ}{dt} = q_i - q_o \quad (8)$$

It is assumed that q_o is proportional to Q

$$q_o = kQ \tag{9}$$

where k is a proportionality constant. Now

$$\frac{dq_o}{dt} = k(q_i - q_o) \tag{10}$$

Integrating with respect to t gives the following solution:

$$q_o = q_i\lfloor - e^{-k(t-t_0)}\rfloor + q_{o(t=0)}e^{-k(t-t_0)} \tag{11}$$

where $q_{o(t=0)}$ is q_o at $t = 0$.

In accordance with the model developed by Huwe et al. (1994), preferential flow was invoked. The water available for discharge was divided into leachate drainage (matrix flow) and preferential discharge by a constant parameter. This parameter, f, was fitted by trial and error. Both discharge components were estimated using Eq. (11). Values of the first order proportionality constants for the leachate drainage (k_l) and fast preferential discharge (k_p) were also determined by trial and error, as were the initial conditions. It was assumed that below a residual water content (or storage capacity) of 10%, no water left the landfill.

3.3. HYDRUS5

HYDRUS5 is a mechanistic model without preferential flow. The combination of Darcy's equation and the equation of continuity yields the well-known Richards equation expressed as:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left(K\frac{\partial h}{\partial z} - K\right) \tag{12}$$

where θ is the volumetric water content ($mm^3\,mm^{-3}$), h the pressure head (mm), K the hydraulic conductivity ($mm\,h^{-1}$), z(mm) a vertical co-ordinate positive downward and t is time (h). The initial landfill condition was expressed by a known pressure head distribution over the vertical depth of the landfill. The boundary condition at the top of the landfill was depicted by a known flux condition, while at the bottom a condition of zero pressure head gradient was imposed to simulate a freely draining profile. Initial and boundary conditions applied to the flow through the landfill were mathematically formulated as:

$$h(z,t) = h_i(z) \qquad t = 0 \tag{13}$$

$$-k\left(\frac{\partial h}{\partial z} - 1\right) = q'(t) \qquad z = 0 \tag{14}$$

$$\frac{\partial h}{\partial z} = 0 \qquad z = L \tag{15}$$

where h_i is the initial pressure head (mm), L the depth of the bottom of the soil and $q'(t)$ is the prescribed flux ($mm\,h^{-1}$) at the surface. Eq. (12), subject to the above initial and boundary conditions, was solved numerically using the HYDRUS5 code (Vogel et al., 1996).

The unsaturated soil hydraulic properties were described by the following equations (van Genuchten, 1980):

$$S_e(h) = \frac{\theta(h) - \theta_r}{\theta_s - \theta_r} = \frac{1}{[1 + |\alpha h|^n]^m} \qquad h < 0 \tag{16}$$

$$\theta(h) = \theta_s \qquad h \geq 0 \tag{17}$$

$$K(h) = K_s S_e^{0.5}[1 - (1 - S_e^{1/m})^m]^2 \qquad h < 0 \tag{18}$$

$$K(h) = K_s \qquad h \geq 0 \tag{19}$$

where α is the inverse of the air-entry value (mm^{-1}), n a pore-size distribution index, S_e the effective water content, $m = 1 - 1/n$, θ_r and θ_s are the residual and saturated water contents ($mm^3\,mm^{-3}$), respectively and K_s is the saturated hydraulic conductivity ($mm\,h^{-1}$).

In HYDRUS5, initial estimates of θ_r, θ_s, α and n were taken from unpublished laboratory desorption curves of intact MSWI bottom ash samples taken from the Landfill Lostorf (Buchter, 1997). The values were $\theta_r = 0.14 mm^3\,mm^{-3}$, $\theta_s = 0.42 mm^3\,mm^{-3}$, $\alpha = 0.0085\,mm^{-1}$ and $n = 1.18$. The SUFI program of Abbaspour et al. (1997) was used to inversely fit the unknown parameters α, n, θ_r, θ_s and K_s as well as the initial pressure head function, h_i, as discussed later. The goal (objective) function was expressed as the sum of square differences between the 5928 h of measured and simulated cumulative discharge from the landfill.

3.4. MACRO, Version 4.0

The program MACRO (Jarvis, 1994) was chosen to simulate flow through the landfill with a preferential component. In MACRO, the equation of flow in

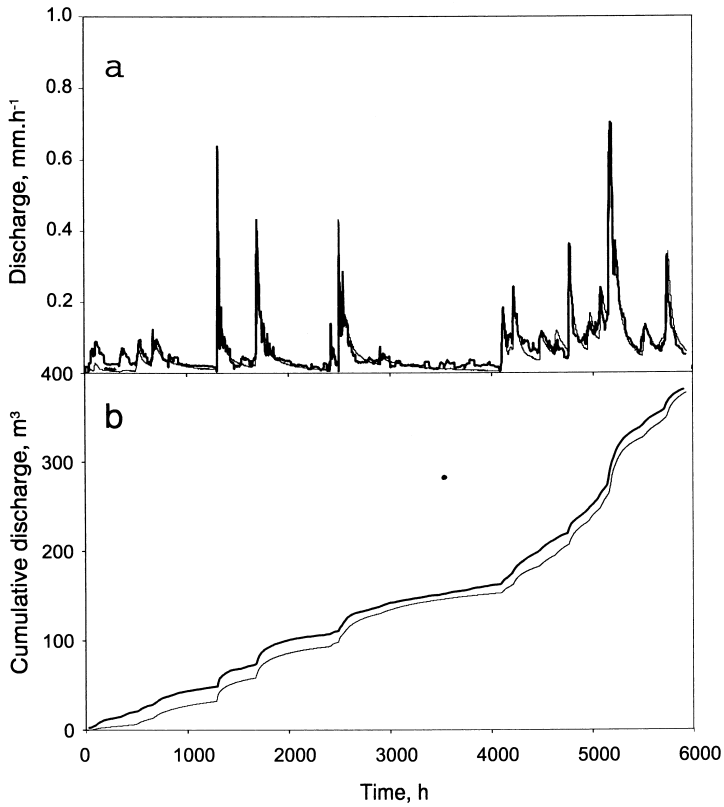

Fig. 1. Comparison of: (a) measured and predicted drainage patterns (thick line); and (b) cumulative discharge for the 8-interval Level 1 neural network model for the 1996 calibration data set.

unsaturated soil is also given by Richards' equation (Eq. (12)) plus an extra term ($\pm S_w$) in the right hand side to account for the exchange of water between macro- and micropore domains. In macropores, a simplified approach is used, where vertical fluxes are predicted as gravity driven laminar flows. For the surface boundary condition, the calculated net precipitation R in a given time interval is divided into an amount taken up by the micropores (I_{mi}) and an excess amount flowing into macropores (I_{ma}):

$$I_{mi} = R \\ I_{ma} = 0; \quad R \leq I_{max} \tag{20}$$

$$I_{mi} = I_{max} \\ I_{ma} = R - I_{mi}; \quad R > I_{max} \tag{21}$$

where I_{max} is the infiltration capacity of the micropores approximated by:

$$I_{max} = \Delta z_1(\theta_{b1} - \theta_1) + \Delta t q_{out(1)} \tag{22}$$

where the subscript 1 refers to the surface soil layer and $q_{out(1)}$ is the water flow rate out of the first layer. The subscript b refers to the conditions at the boundary between soil matrix and preferential flow region (Jarvis, 1994). As in the HYDRUS5, the initial condition was furnished by a known pressure head distribution to be discussed later.

In the macropores, gravity flow of water is assumed and hence pressure head h is not needed, while in the micropores retention and flow curves for a two-domain case are of the types given by Brooks and Corey (1964) and Mualem (1976), respectively, expressed as:

$$h_{mi} = h_b S_{mi}^{-1/\lambda} \tag{23}$$

Table 2
The results of statistical comparisons between measured and predicted discharge

Model	Calibration SSQ	Validation SSQ
Neural network model 8-interval, Level 1	7.42	15.1
Linear storage model	40.4 (29.4.96–31.8.96) 7.2 (1.9.96–31.12.96)	8.2
HYDRUS5	27.6	32.1
MACRO	10.1	41.1

$$K_{mi} = K_b S_{mi}^{n+2+2/\lambda} \tag{24}$$

$$K_{ma} = K_{s(ma)} S_{ma}^{n^*} \tag{25}$$

where h_b is the air entry pressure, assumed to be identical with the pressure head (mm) at the boundary of micro- and macropores, λ the pore size distribution index in the micropores, K_b the hydraulic conductivity at the boundary between macro- and micropores, n the tortuosity factor in the micropores and n^* an empirical exponent accounting for pore size distribution in the macropores. S_{mi} and S_{ma} are the effective saturations in micro- and macropores, respectively, given by:

$$S_{mi} = \frac{\theta_{mi} - \theta_r}{\theta_b - \theta_r} \tag{26}$$

and

$$S_{ma} = \frac{\theta_{ma}}{e_{ma}} \tag{27}$$

where e_{ma} is the macroporosity.

The landfill in MACRO was divided into 10 layers (0–20, 20–40, 40–60, 60–100, 100–200, 200–300, 300–400, 400–500, 500–550 and 550–600 cm). The values of the parameters θ_s and θ_r were adopted from the results of the HYDRUS5 fitting procedure. The parameters θ_i, θ_b, K_b, λ, n and n^* were fitted with the program SUFI as described above for HYDRUS5. The values of these parameters in the different layers were allowed to vary in three groups comprising the top three layers, the middle three layers and the four bottom layers. This grouping was based on the observed heterogeneity in the landfill profile. Otherwise, the parameters were assumed to be the same in all layers. Initial values were adopted from the MACRO manual (Jarvis, 1994) assuming physical properties of a medium-grained soil, as were parameters that are not specifically mentioned here. Shrinkage was not considered.

4. Results and discussions

4.1. Neural network simulations

Results for the 8-interval model calibration using the Level 1 approach of the 1996 data set are shown in Fig. 1a and b together with field values. The agreement between model results and field data improves with an increasing number of time intervals. The SSQ is 33.3 with two time intervals (6 h of history) and decreases linearly for interval 7 to a value of 6.45 (two weeks of history, Table 2). Adding intervals 8 and 9 (3 and 4 weeks of history) does not significantly improve the prediction of drainage. The 8-interval model time series predicts the total discharge over the modelled time period well and shows the rapid responses to rain events, though predicted values did not become as smooth as the measured drainage. The agreement between the predicted and measured cumulative water volume is excellent. Oscillations in predicted discharge were observed for the 2- and 4- interval data set (not shown). These were caused by the daily evaporation pattern included in $\boldsymbol{H}_t$ when there is little or no measured precipitation. Sometimes increases in drainage were simulated where none were measured.

For Level 2, the drainage rate at time t was added to the input data as explicit information about the internal state of the system. The neural network models with measured drainage rates improved SSQ by a factor of 50–100 in comparison with Level 1 (Table 1). The measured and predicted time series became almost indistinguishable (not shown). The independence of SSQ on the number of intervals indicates that the history of rainfall is insignificant in comparison to the drainage at time t. It should, however, be noted that when the previously predicted drainage is used to predict the next time step, the fit is poor. The SSQ ranges from 400 to 110,000. This can be explained by positive feedback. It may be concluded that models of Level 2 are unreliable to simulate drainage patterns, though they could still be useful

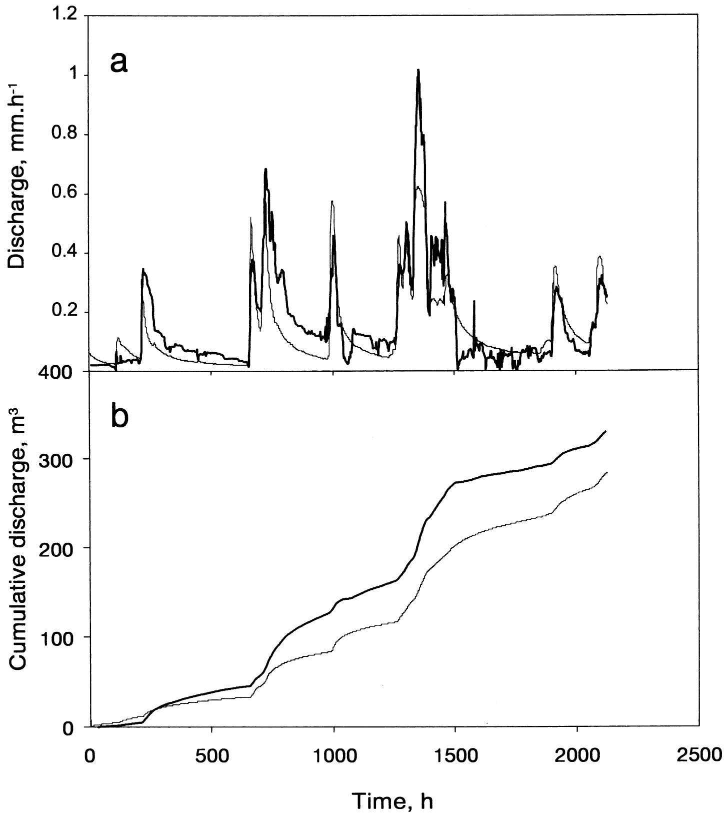

Fig. 2. Comparison of: (a) measured and predicted drainage patterns (thick line); and (b) cumulative discharge for the 8-interval Level 1 model neural network model for the 1995 test data set.

to assimilate measured drainage data for real-time application.

Level 3 tries to solve some of the positive feedback problems of Level 2 by using storage of water in the profile as a negative feedback. If the neural network models of Level 3 would somehow over predict drainage, this would lead to a decrease in simulated stored water that in turn would immediately lead to a decrease in the simulated drainage at the next time step. Table 2 shows that the results of the Level 3 models are very similar to those of the Level 1 models. Values of SSQ decrease when more net precipitation history is used. Storage history (similar to the precipitation history) could further improve the usability of Level 3 beyond that of Level 1. In our analyses, we noted that Level 3 models provided a relatively good description of drainage in the autumn period, but sometimes poorly predicted outflow in summer (not shown). The Level 1 approach is simple and its use justifiable.

The model results of the 1995 test data set using the parameters determined from the 8-interval Level 1 model calibration of the 1996 data are shown in Fig. 2a. The fit is quite good (SSQ = 15.1) (Table 2). The most important features of the discharge have been modelled, though the model data is not as smooth as the measured data. Also, there is an over-prediction of the total volume of water discharged of approximately 18% (Fig. 2b).

4.2. Linear storage simulations

Modelled total discharge is compared to measured discharge for the 1996 data set in Fig. 3a and b. The best fit was obtained with values of $k_p = 0.02\ h^{-1}$, $k_l = 0.0012\ h^{-1}$ and $f = 0.6$. Parameter k_p was fitted on the

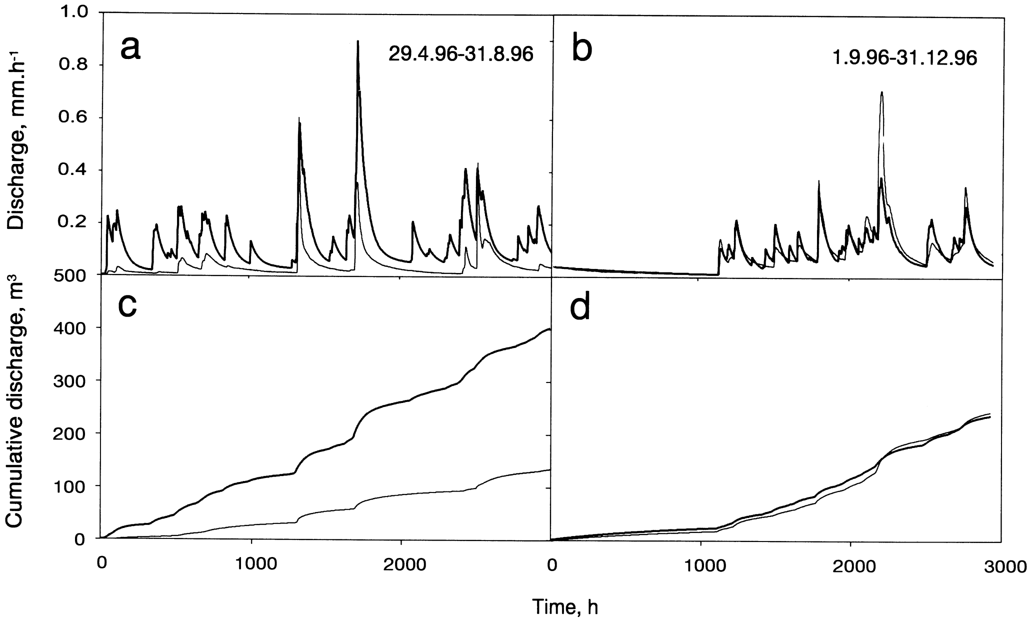

Fig. 3. Comparison of measured and predicted drainage patterns (thick line) using the linear storage model for: (a) 28.4.96–31.8.96; (b) for 1.9.96–31.12.96; (c) cumulative discharge for the former period; and (d) cumulative discharge for the latter period.

recession curve of the discharge response to an average event (with a discharge peak of approx. 0.4 mm h^{-1}) since it had earlier been found that k_p is proportional to the maximum discharge associated with a rain event (Johnson et al., 1998). Thus, using an average value of k_p there is a tendency to overestimate small rain events and underestimate large ones. A value of k_l was obtained from discharge recession curves during periods unaffected by rain events. The 1996 data set was divided into two subsets, 29 April to 31 August 1996 and 1 September to 31 December 1996 and the model calculations carried out with the above-mentioned parameters. This was done because, as can be seen from Fig. 3c and d, the discharge was over-predicted for the summer data subset (SSQ = 40.4) (Table 2) but gave a very good fit for the second data subset (SSQ = 7.2). The reason for the difference in fit between the two subsets is most probably due to problems in dealing with water retention. This simple model assumes that the bottom ash has a given retention capacity. No water leaves the landfill before this given value has been achieved and from that point on the landfill "reservoir" is full. This approach is clearly not adequate for fully describing water flow, particularly in dry summer months

The fit of the 1995 test data set (Fig. 4a) using the parameters fitted for the 1996 data set was good (SSQ = 8.2) and was comparable to the 1996 winter data subset. The cumulative discharge was over-estimated by 18% (Fig. 4b).

4.3. Simulations with HYDRUS5

It is important to initially emphasise that the simulations with the mechanistic models in this study were conducted with the minimum of required information. The initial pressure head h_i, as well as the parameters α, n, θ_r, θ_s and K_s were first fitted on the measured cumulative discharge assuming a uniform distribution of the initial pressure head in the landfill. This simulation led to a very smooth outflow response, not resembling the measurements.

At the beginning of the simulation period in April 1996 the landfill was in a very dry state. In order to obtain values for the initial water content, estimates were made using the parameters obtained by the initial fitting. The flow 3000 h beyond the end of the simulation period was modelled without rainfall until the discharge rates were equal to the measured discharge at the beginning of the simulation period

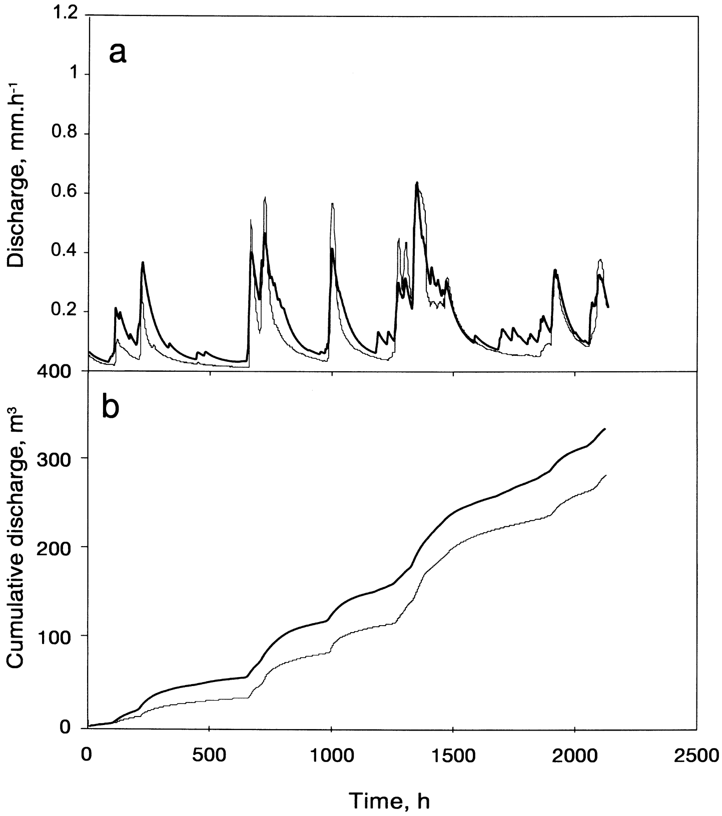

Fig. 4. Comparison of: (a) measured and predicted drainage patterns (thick line); and (b) cumulative discharge for the linear storage model for the 1995 test data set.

in April. Using the pressure head values at this stage as the initial values, the inverse estimation of the hydraulic parameters was once again performed. The results of simulations were greatly enhanced by the new non-uniform-initial-pressure-head data. Fig. 5a shows the measured and simulated hourly discharge as a function of time, while Fig. 5b illustrates the measured and simulated cumulative discharge. Although there are major differences in the hourly discharge rates of measured and simulated data (SSQ = 27.6) (Table 2), the cumulative values are rather closely matched. The estimated values of the parameters were $\alpha = 0.013\ \mathrm{mm}^{-1}$, $n = 1.11$, $\theta_r = 0.15\ \mathrm{mm}^3\ \mathrm{mm}^{-3}$, $\theta_s = 0.28\ \mathrm{mm}^3\ \mathrm{mm}^{-3}$, and $K_s = 290\ \mathrm{mm\ h}^{-1}$.

Parameters obtained by fitting the 1996 discharge data were tested by predicting the hourly discharge rates measured in 1995 (Fig. 6a). Again, the simulation smoothes the hourly observed fluctuation, indicating that a fast flow component is missing in the model. The agreement between modelled and measured discharge is fair (SSQ = 32.1). The discrepancy in the hourly discharge rates indicates the possibility of a fast flow component conducted by preferential flow paths.

4.4. Simulations with MACRO

Simulation with MACRO required knowledge of the parameters θ_i, θ_s, K_b, λ, n and n^* used in Eqs. (20)–(27). Before inversely fitting the parameters, and using parameters based on literature values the simulation with macro was very poor. After fitting the parameters we obtained the following average values: $\theta_i = 0.24\ \mathrm{mm}^3\ \mathrm{mm}^{-3}$, $\theta_s = 0.28\ \mathrm{mm}^3\ \mathrm{mm}$,

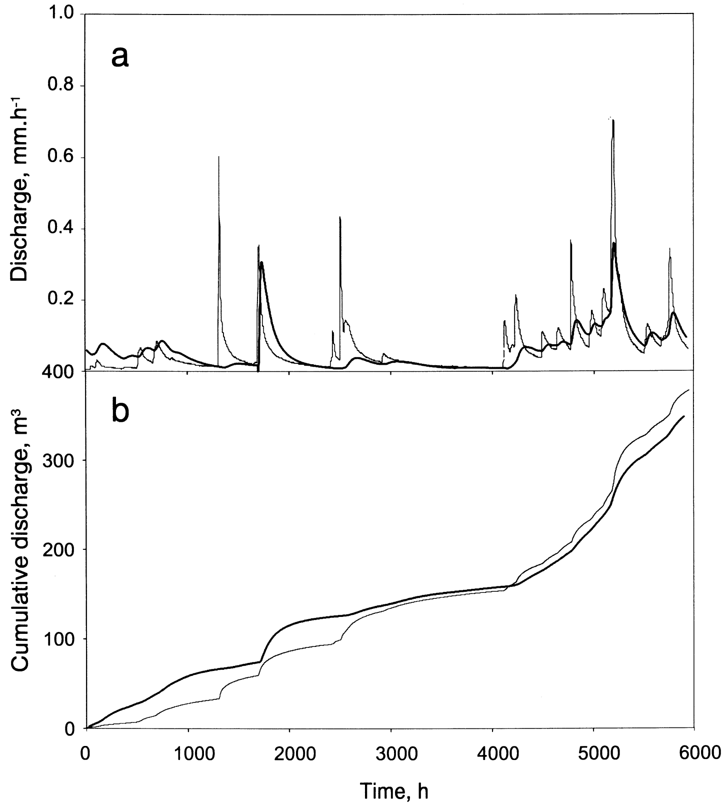

Fig. 5. Comparison of: (a) measured and predicted drainage patterns (thick line); and (b) cumulative discharge for the HYDRUS5 model for the 1996 calibration data set.

$K_b = 0.4\ \mathrm{mm\ h^{-1}}$, $\lambda = 0.36$, $n = 0.086$ and $n^* = 2.56$ and a excellent agreement between simulated and measured discharges (Fig. 7a, SSQ = 10.1). The response to the net rainfall of the modelled discharge is good, though there is a slight over-response to rain events. The baseline flow, observed best during dry periods, is slightly high and may be the cause of the delayed response to the onset of rain after 4000 h. Nevertheless, the modelled cumulative discharge is in good agreement with the measured value (Fig. 7b).

The visual agreement between modelled and measured discharge data is very good for the 1995 test data set (Fig. 8a), though the SSQ is 41.1. The baseline flow of the model is close to but often lower than the measured data and there is a discrepancy between modelled and measured peak discharges. This leads to an underestimation of cumulative discharge by almost 15% (Fig. 8b). A reason for the poor validation result may be that the parameters obtained by inverse modelling may have been too conditioned on the calibration data set, and not widely applicable to other years with different climatic conditions.

4.5. Preferential flow modelling

Fig. 9 illustrates components of the total discharge for the 1995 test data set. Two components are assumed to make up the total discharge: flow through preferential paths and flow through the matrix (leachate discharge). The relatively fast preferential flow passes through the landfill without much contact with the waste material; hence, the discharge water has almost the same electrical conductivity as the rainwater. In contrast, the flow through the matrix becomes in intimate and prolonged contact with the

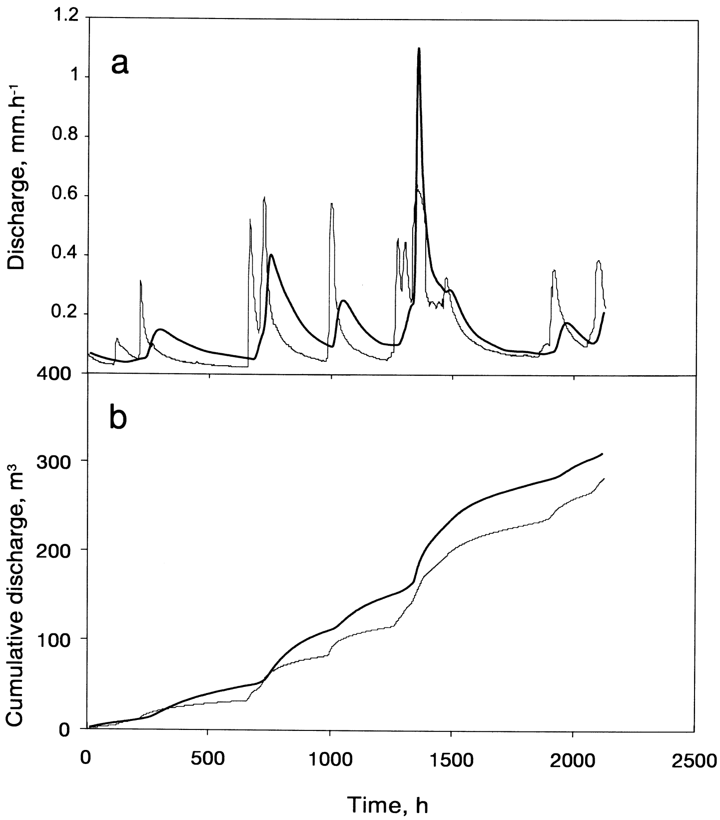

Fig. 6. Comparison of: (a) measured and predicted drainage (thick line) patterns; and (b) cumulative discharge for the HYDRUS5 model for the 1995 test data set.

waste material, dissolved salts, and contaminants. Fig. 9a shows the total measured discharge and the leachate component of flow estimated using electrical conductivity. As noted in Johnson et al. (1998), the leachate component of flow appears to increase during rain events as might be caused by a washout or a piston-flow effect. The empirical linear storage model and the mechanistic model MACRO both predicted a peak-discharge response to the rain events quite well. However, the leachate discharge component of both models appeared to be much smoother than that estimated from tracer studies using electrical conductivity, though the linear storage model does show a slight increase in leachate discharge, in keeping with the conductivity results, in response to a rainfall.

It should be noted, however, that electrical conductivity probably underestimates leachate discharge in conditions where the water content of the MSWI bottom ash is high (Johnson et al., 1998). The results of tracer studies comparing electrical conductivity and $^{18}O/^{16}O$ indicate that preferential flow is overestimated by electrical conductivity in winter months. Under such conditions, a clear distinction between leachate drainage and preferential flow becomes difficult. Nevertheless, it is clear that neither of the models exactly reflects the field data.

The use of electrical conductivity in the fitting procedure may nevertheless be of value. Since many contaminant concentrations are directly proportional to electrical conductivity, such a procedure would enable the modeller to quantify the contaminant leaching process. For illustration a comparison is made between cumulative leachate discharge estimated from electrical conductivity and an estimate based on the assumption that leachate discharge is

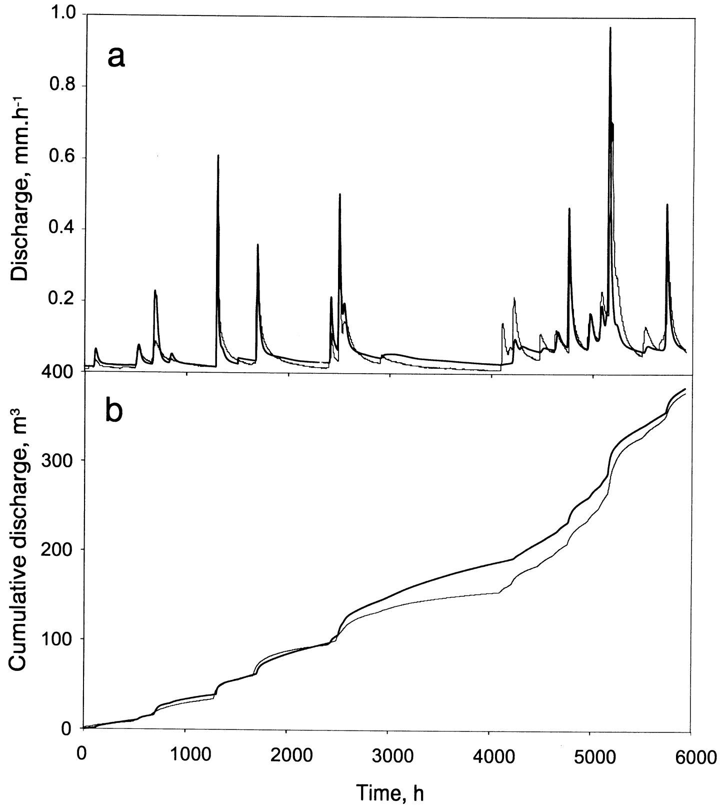

Fig. 7. Comparison of: (a) measured and predicted drainage patterns (thick line); and (b) cumulative discharge for MACRO model for the 1996 calibration data set.

constant and approximately equal to the total discharge under dry conditions. The latter is approximately three to four times smaller and would lead to a significant underestimation of the leaching process. It is therefore important to determine, as closely as possible, the contribution of leachate discharge to the total discharge.

4.6. Model comparison

The comparison of empirical and deterministic approaches to modelling landfill drainage has shown that the empirical approaches can give better fits (Table 2), though it is unlikely that the models developed in this paper can be applied directly to other sites. The neural network approach is a flexible technique that may be adapted as a data-assimilation or predictive tool. Problems may arise, however, due to the non-linearity of the landfill system, whereby a certain internal state in the landfill (i.e. the water content) can produce different rates of discharge for similar rain events. This is certainly the case for the linear storage model. While the interpretation of the winter 1996 data set and the prediction of the winter 1995 data set are both good, interpretation of the summer 1996 data set is poor because, with the same parameter values, the rate of discharge is overestimated. The changing water content of the landfill body appears to cause problems for both these empirical approaches, though the neural network approach has a greater development potential.

The relatively poor fit of HYDRUS5, the deterministic model without preferential flow, shows that indeed a portion of the flow is conducted through preferential paths and that it must be taken into account. An interesting observation here is that inverse parameter fitting could not be of a substitute for the accounting of an important hydrological

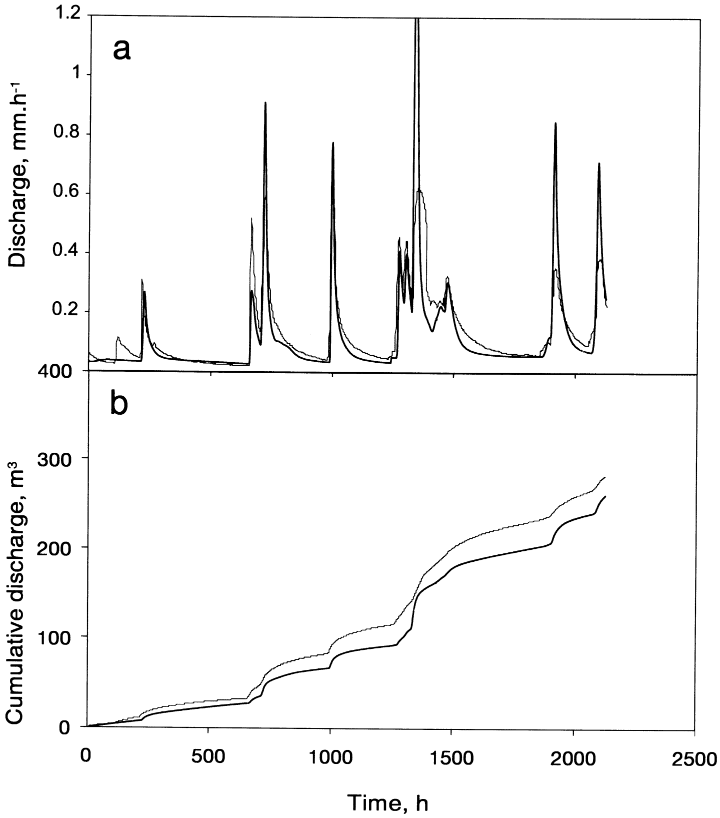

Fig. 8. Comparison of: (a) measured and predicted drainage patterns (thick line); and (b) cumulative discharge for the MACRO model for the 1995 test data set.

process, as it is often believed to be. Although the quantity of flow passing through preferential paths may not be important to the long-term water balance of a landfill, it appears to play a significant role for the adequate prediction of instantaneous flow and for the chemical loading of the water. However, taking account of preferential flow increases the number of unknown parameters pertaining to the physical properties of the landfilled material. It has become generally accepted that such data must be fitted. Fitting greatly improved the results in our case, but it also means that, because of the possibility of covariance, the values of the individual parameters have no physical meaning in themselves when fitted in this way and should not be assessed individually. Further, the mechanistic models would greatly benefit from improved monitoring procedures. Knowledge of the initial and boundary conditions, pressure head or water content data from the landfill profile as a function of time could be profitably used for long-term prediction purposes.

Since most questions relating to landfill leachate are related to chemical loading, an assessment of preferential flow using a suitable tracer would be an important step forward, whether an empirical or mechanistic approach is employed. It is not possible to exclude one approach in favour of another. The choice of approach depends on the type of answer sought and should be chosen with care. Finally, it is realised that prediction of drainage discharge is only an intermediate step in the analysis of a landfill. The important end result is the prediction of chemical transport mobilised in the ash formation of the landfill. Since the relationship between discharge and the chemical load that it carries is not straightforward due to different flow pathways and, hence, the different

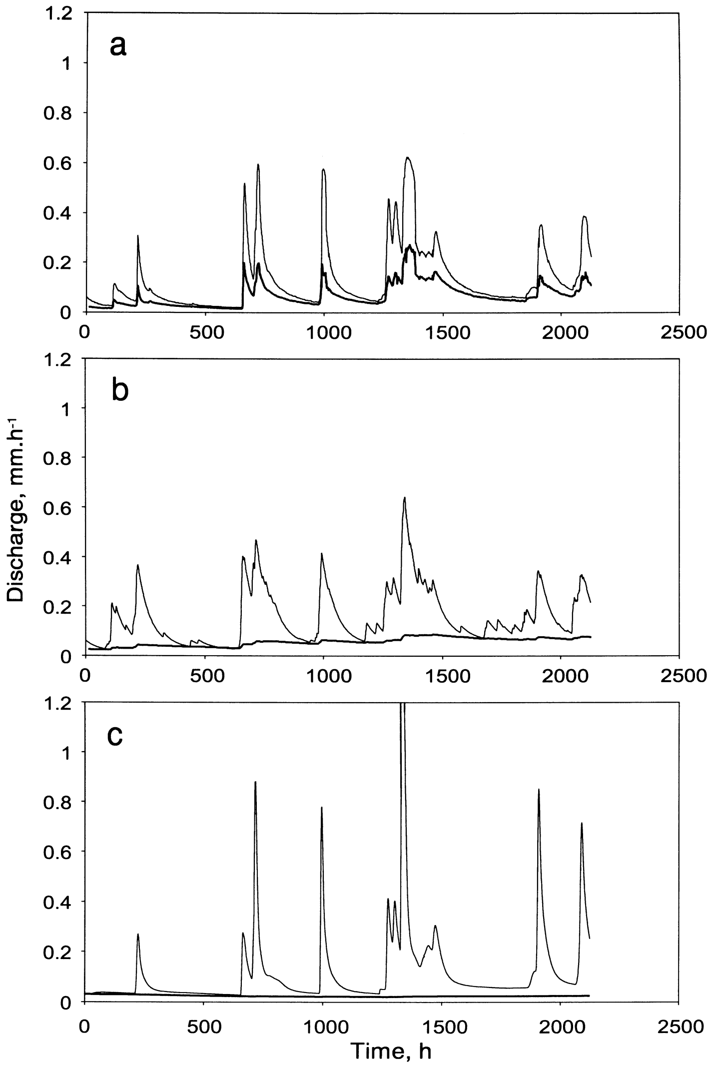

Fig. 9. Comparison of (a) measured total discharge and leachate drainage (matrix flow) with (b) modelled total discharge and leachate drainage using the linear storage and (c) modelled total discharge and leachate drainage using the MACRO model for the 1995 test data set.

residence time of the water within the landfill, direct projection of the drainage results to the transport is not possible. A model producing good drainage discharge results based on calibration of hydraulic or other model parameters may not necessarily produce a good prediction of the chemical load in the drainage water. For this reason our description of the performance of the models as good or poor must be understood within the context of this paper which was to simulate the dynamics of the drainage discharge. Analysis of the chemical transport will be discussed in a separate work.

5. Conclusions

In this article, we tested the ability of a neural network model, a hydrological linear storage model, and two mechanistic models with and without preferential flow to simulate hourly discharge patterns of a landfill near Buchs, Switzerland. We found after calibration, the discharge predicted by the functional models to match more closely the discharge behaviour of the landfill. The linear storage mode, however, could not cope with the non-linearity of the system that was caused by seasonal changes in water content of the bottom ash material. The fit of the neural networks model to the data improved with increasing prior information but was less smooth than the measured data. The program HYDRUS5 could not capture all the dynamics of the discharge from the landfill due what is believed to be a preferential component, but MACRO which includes a preferential component, performed much better. The model MACRO, however, produced the worst validation results indicating that the parameters obtained by inverse modelling may have been too conditioned on the calibration data set and not widely applicable to other years with different climatic conditions.

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